Long Range Channel Prediction for Adaptive OFDM Systems

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***Abstract*— In this paper, different techniques for long-range channel prediction for OFDM systems are investigated. Frequency domain channel prediction on each OFDM data subcarrier is first explored, and it is shown that the optimum prediction filter depends only on the time-domain channel statistics for the wide-sense stationary uncorrelated scattering (WSSUS) wireless channel. Frequency domain prediction on the pilot subcarriers is investigated next, where the optimum prediction filter is determined for each pilot subcarrier, and is reused for all the nearby data subcarriers. Finally, time-domain channel prediction on the multipath taps is explored. It is shown that frequency domain prediction on the pilot subcarriers performs almost identically to prediction using all subcarriers. Furthermore, it is also shown that time-domain prediction outperforms the frequency domain prediction methods.**

I. Introduction

Adaptive OFDM systems overcome the limitation of conventional OFDM by allowing the transmitter to vary the power, modulation, and coding on each subcarrier depending on the current channel state information (CSI) [1]. This requires the transmitter to have knowledge of the CSI, which can be obtained through feedback from the receiver's channel estimates, or through its own estimates in a time division duplex (TDD) reciprocal channel. In high mobility environments, where the Doppler frequency is high and the channel changes rapidly, the CSI used by the transmitter would be outdated due to the processing and feedback delays.

In [2], delayed CSI was shown to negatively impact the capacity and bit error rate of the adaptive OFDM system. Furthermore, it was shown that the use of channel prediction can improve the performance of the system. In [3], channel prediction over a longer range was shown to improve the performance of adaptive OFDM in a low-mobility environment. In that system, the coefficients of a linear predictor for each OFDM subcarrier was updated for each new block of observed symbols. In [4], decision-directed and adaptive short-term channel prediction on the time-domain channel taps were proposed. Their approach uses an IFFT/FFT pair to derive the time-domain channel taps, perform the prediction, and then return to the frequency domain. In [5], an unbiased channel power predictor was applied to the time-domain channel taps, and a preliminary evaluation of frequency domain channel prediction on all the subcarriers was also presented.

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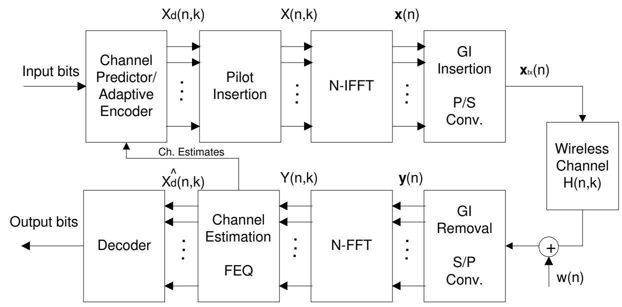

Fig. 1. Adaptive OFDM System Block Diagram

In the prior work in this area, it was not clear whether frequency domain prediction on all the tones, frequency domain prediction on the pilot tones, or time-domain prediction is best. This paper analyzes and compares the performance of these three different channel prediction strategies. These approaches are compared in terms of complexity and normalized mean-squared error performance (NMSE). It is shown through NMSE derivations and simulation results that frequency domain prediction on the pilot subcarriers performs almost identically to prediction using all subcarriers. Furthermore, it is also shown that time-domain prediction outperforms the frequency domain prediction methods.

II. System Model

A. OFDM System

The adaptive OFDM system model considered in this paper is given in Fig. 1. The input bits are initially mapped by a bank of adaptive encoders into N_d complex data symbols $X_d(n,k)$ which corresponds to the kth subcarrier in the nth OFDM block. The constellation density for each encoder would depend on the predicted state of the wireless channel, in which various bit and power allocation strategies may be used to either maximize the data rate or to minimize the power given a bit error rate (BER) constraint. The next block inserts N_p pilot symbols $X_p(n,k)$ which are known to both transmitter and receiver and are used primarily for channel estimation and/or synchronization. It also inserts N_g guard symbols $X_g(n,k) = 0$ at the edges of the OFDM symbol which allows for the OFDM signal to naturally decay and obey spectral mask constraints. The combination of data, pilot, and guard symbols form the N-subcarrier OFDM symbol $X(n,k)$. This is subsequently transformed into a time domain sequence $\{x_i(n)\}_{i=1}^{N}$ using the N-point IFFT.

Ignoring the effects of intersymbol and intercarrier interference, the received signal for the kth subcarrier in the nth OFDM block is $Y(n,k) = H(n,k)X(n,k) + W(n,k)$ where $H(n,k)$ and $W(n,k)$ are the frequency domain channel gain and the additive white Gaussian noise (AWGN) respectively. The channel estimation block then takes $Y(n,k)$ as input and forms the channel estimates $\hat{H}(n,k)$ to detect the transmitted sequence as $\hat{X}(n,k) = Y(n,k)/\hat{H}(n,k)$. These channel estimates are then fed back to the transmitter with a delay Δ, where the channel prediction block would generate the predicted channel estimates $\hat{H}(n+\Delta,k)$ for adaptation.

B. Wireless Channel

The complex baseband representation of the time-varying wireless channel is given by [6]

$$h(t,\tau) = \sum_{i=0}^{r-1} \alpha_i(t)\delta(\tau - \tau_i) \tag{1}$$

where τ_i is the delay and $\alpha_i(t)$ is the complex amplitude of the ith multipath, and where there are r total propagation paths. The $\alpha_i(t)$'s are assumed to be wide sense stationary, narrowband complex Gaussian random processes, which are bandlimited by the Doppler frequency f_d and independent for each path i. It is also assumed that $h(t,\tau)$ is constant within one OFDM symbol duration $T_{sym} = 1/F_{sym}$.

Taking the Fourier transform of (1), we get the frequency response of the time-varying channel

$$H(t,f) = \sum_{i=0}^{r-1} \alpha_i(t)e^{-j2\pi f\tau_i} \tag{2}$$

Assuming that the OFDM system with symbol period T_{sym} and subcarrier spacing Δf have proper cyclic extension and sample timing, it was shown in [7] that the sampled channel frequency response at the kth tone of the nth OFDM block can be expressed as

$$\begin{aligned} H(n,k) &\triangleq H(nT_{sym}, k\Delta f) \\ &= \sum_{i=0}^{N_t-1} h(n,i)e^{-j2\pi ki/N} \end{aligned}$$

where $h(n,i) \triangleq h(nT_{sym}, iT_s)$, with $T_s = 1/\Delta f$ denoting the sampling period of the system. Furthermore, the $h(n,i)$ for $i = 0,1,\ldots,N_t-1$ are wide sense stationary (WSS), independent, narrowband complex Gaussian processes, with average power σ_i^2 and number of taps ($N_t \ll N$) that depend on the delay profiles and dispersion of the wireless channel.

We further assume that each $h(n,i)$ has the same normalized correlation function $r_h(m)$ for all i, i.e.

$$r_{h_i}(m) \triangleq \mathbb{E}\{h(n+m,i)h^*(n,i)\} = \sigma_i^2 r_h(m) \tag{3}$$

and that the total power of the path gains are normalized to 1, i.e., $\sum_i \sigma_i^2 = 1$.

Thus, the correlation function for the frequency response for different OFDM blocks and tones can be written as

$$\begin{aligned} r_H(m,l) &\triangleq \mathbb{E}\{H(n+m,k+l)H^*(n,k)\} \\ &= r_h(m)r_f(l) \end{aligned} \tag{4}$$

where $r_h(m) = \mathbb{E}\{h(n+m)h^*(n)\}$ is the time correlation function for the WSS time-domain channel taps and $r_f(l) = \sum_{i=0}^{N_t-1} \sigma_i^2 e^{-j2\pi li/N}$ is the frequency correlation function where σ_i^2 is the average power for the ith tap. Therefore the correlation function is time-frequency separable, where clearly $r_h(0) = r_f(0) = 1$.

III. Channel Prediction for OFDM Systems

In this section, we discuss the three different OFDM channel prediction schemes.

A. Prediction over all the tones

Define the mean squared error (MSE) of the predicted frequency domain channel as

$$\varepsilon(n) = \frac{1}{N}\sum_{k=0}^{N-1} \mathbb{E}\{|H(n+\Delta,k) - \hat{H}(n+\Delta,k)|^2\} \tag{5}$$

and the predicted channel response as

$$\hat{H}(n+\psi d,k) = \sum_{l=0}^{p-1} w_k(l)\hat{H}(n-ld,k) \tag{6}$$

where

$$\hat{H}(n-ld,k) = H(n-ld,k) + E(n-ld,k) \tag{7}$$

are the past noisy estimates of the channel acquired at the downsampled rate $F_d = F_{sym}/d$ where d is a positive integer denoting the downsampling factor. For generality, no particular channel estimation method is assumed, and the channel estimation error $E(n,k)$ is assumed to be a zero mean Gaussian random variable with variance σ_{est}^2. It is also assumed that this error is independent for different ns and ks, and is uncorrelated with all $H(n,k)$. The w_k's are the N 1-D Wiener prediction filter coefficients for each tone k which exploits the time-domain correlation of the kth OFDM tone [1].

For notational convenience, we assumed that we wish to predict the channel response at a future time that is a multiple of the downsampling factor d, i.e. $\Delta = \psi d$, and we would like to predict ψ steps ahead. Prediction at instances not a multiple of downsampling rate could be easily accomplished through interpolation.

[1]Although a 2-D Wiener filter which exploits both time and frequency domain correlation would in general achieve a lower MSE, it was shown in [8] for the case of channel estimation that separate time and frequency domain filters can instead be used without much performance degradation.

Since (5) is clearly a separable function, we can treat each tone as a separate minimization problem. Using the orthogonality principle [9] on a particular tone k gives us

$$\mathbb{E}\{(H(n+\psi d,k)-\hat{H}(n+\psi d,k))\hat{H}^*(n-ld,k)\}=0, \quad l=0,\cdots,p-1 \tag{8}$$

Substituting (6) into (8), and using (7), we get the optimum prediction filter as

$$\mathbf{w}_k=(\mathbf{R}_{H_k}+\sigma_{est}^2\mathbf{I})^{-1}\mathbf{r}_{k,\psi} \tag{9}$$

where

$$\mathbf{w}_k=[w_k(0) \quad w_k(1) \quad \cdots \quad w_k(p-1)]^T \tag{10}$$

$$\mathbf{R}_{H_k}= \begin{bmatrix} r_{H_k}(0) & r_{H_k}^*(d) & \cdots & r_{H_k}^*(d(p-1)) \\ r_{H_k}(d) & r_{H_k}(0) & \cdots & r_{H_k}^*(d(p-2)) \\ \vdots & \vdots & \ddots & \vdots \\ r_{H_k}(d(p-1)) & r_{H_k}(d(p-2)) & \cdots & r_{H_k}(0) \end{bmatrix} \tag{11}$$

$$\mathbf{r}_{k,\psi}=[r_{H_k}(\psi d) \quad r_{H_k}((\psi+1)d) \quad \cdots \quad r_{H_k}((\psi+p-1)d)]^T \tag{12}$$

and

$$\begin{aligned} r_{H_k}(m) &\triangleq \mathbb{E}\{H(n+m,k)H^*(n,k)\} \\ &\approx \frac{1}{M}\sum_{i=0}^{M-1-m}\hat{H}(di+m,k)\hat{H}^*(di,k) \end{aligned} \tag{13}$$

where the autocorrelation function estimate from M previous downsampled channel estimates [9] is used in (13). Substituting the optimum filter coefficients (9) into mean squared error function (5) gives the minimum mean squared error (MMSE)

$$\varepsilon_{min,f}=\frac{1}{N}\sum_{k=0}^{N-1}(r_{H_k}(0)-\mathbf{r}_{k,\psi}^H(\mathbf{R}_{H_k}+\sigma_{est}^2\mathbf{I})^{-1}\mathbf{r}_{k,\psi}) \tag{14}$$

.

B. Prediction using the pilot tones

In the previous method described, notice that (13) is actually an estimate for the time-domain autocorrelation function of the multipath taps given in (4), i.e. since $r_{H_k}(m)=r_H(m,0)=r_h(m)$. Hence, determining w_k's separately for all N subcarriers is unnecessary, since the optimum prediction filter is theoretically the same for all subcarriers. However, non-ideal conditions such as correlated scattering and differential Doppler could potentially degrade the performance when only one prediction filter is used for all subcarriers.

A potential tradeoff that can be made is to design $N_p \ll N$ prediction filters corresponding to the pilot subcarriers in the OFDM symbol. These filters are then reused by the data subcarriers nearest to the given pilot subcarrier predictor.

The prediction filter design equations are the same as for the all-tone prediction as given in (9), except that (13) should be changed to

$$\begin{aligned} r_{H_k}(m) &\approx \frac{1}{M}\sum_{i=0}^{M-1-m}\hat{H}(di+m,k')\hat{H}^*(di,k'), \\ & \qquad k'=\arg\min_{l\in\mathcal{N}_p}|l-k| \end{aligned} \tag{15}$$

where $\mathcal{N}_p$ is the set of subcarrier indices corresponding to the pilot tones.

The MMSE is also given by (14), but we expect it to be slightly greater than the MMSE for the all-tone prediction because of the approximation in (15).

C. Prediction on the time-domain channel taps

Another approach would be to perform prediction on the N_t time-domain channel taps. Consider the N-length vector of the time domain channel taps as the IFFT of the frequency domain channel estimates (7)

$$\begin{aligned} \hat{\mathbf{h}}(n) &= \mathbf{W}_N^H\hat{\mathbf{H}}(n) \\ &= \mathbf{W}_N^H(\mathbf{H}(n)+\mathbf{E}(n)) \\ &= \mathbf{h}(n)+\mathbf{e}(n) \end{aligned} \tag{16}$$

where $\mathbf{W}_N^H$ is the IDFT matrix and $\mathbf{h}(n)$ is the time-domain channel tap vector. The noise vector $\mathbf{e}(n)$ is uncorrelated with $\mathbf{h}(n)$ and has elements that are also independent and identically distributed Gaussian random variables with zero mean and variance σ_{est}^2, since the IDFT is an orthogonal linear transformation. Let $\mathcal{N}_t$ be the set of indices that correspond to the N_t elements with the highest energy in $\hat{\mathbf{h}}(n)=[\hat{h}(n,0),\ldots,\hat{h}(n,N-1)]$. We assume that we have knowledge of the number of multipath taps N_t, and thus we can predict on only the N_t highest energy taps and still have the information about the channel. Determining the Wiener prediction filter for each $i\in\mathcal{N}_t$, we have

$$\mathbf{w}_i=(\mathbf{R}_{h_i}+\sigma_{est}^2\mathbf{I})^{-1}\mathbf{r}_{i,\psi} \tag{17}$$

where $\mathbf{R}_{h_i}$ and $\mathbf{r}_{i,\psi}$ are the autocorrelation marix and cross correlation vector similarly defined as in (11) and (12), but with autocorrelations

$$\begin{aligned} r_{h_i}(m) &\triangleq \mathbb{E}\{h(n+m,i)h^*(n,i)\} \\ &\approx \frac{1}{M}\sum_{l=0}^{M-1-m}\hat{h}(ld+m,i)\hat{h}^*(ld,i) \end{aligned} \tag{18}$$

For the time domain channel taps that are not in $\mathcal{N}_t$, we simply consider them to be zero, and thus the predicted time-domain channel response is

$$\hat{h}(n+\psi d,i)=\begin{cases} \sum_{l=0}^{p-1} w_i(l)\hat{h}(n-ld,i), & i\in\mathcal{N}_t \\ 0, & \text{otherwise} \end{cases} \tag{19}$$

The MMSE for each of the time domain channel taps can then be written as

$$\varepsilon_{min,i} = r_{h_i}(0) - \mathbf{r}_{i,\psi}^H(\mathbf{R}_{h_i} + \sigma_{est}^2\mathbf{I})^{-1}\mathbf{r}_{i,\psi} \tag{20}$$

.

Considering the MSE of the predicted frequency domain channel response (5) written in vector form,

$$\begin{aligned}\varepsilon_{min,t} &= \frac{1}{N}\mathbb{E}\{(\mathbf{H}-\hat{\mathbf{H}})^H(\mathbf{H}-\hat{\mathbf{H}})\}\\ &= \frac{1}{N}\mathbb{E}\{(\mathbf{W}_N(\mathbf{h}-\hat{\mathbf{h}}))^H(\mathbf{W}_N(\mathbf{h}-\hat{\mathbf{h}}))\}\\ &= \frac{1}{N}\mathbb{E}\{(\mathbf{h}-\hat{\mathbf{h}})^H(\mathbf{h}-\hat{\mathbf{h}})\}\\ &= \frac{1}{N}\sum_{i=1}^{N_t-1}\left(r_{h_i}(0) - \mathbf{r}_{i,\psi}^H(\mathbf{R}_{h_i} + \sigma_{est}^2\mathbf{I})^{-1}\mathbf{r}_{i,\psi}\right)\end{aligned} \tag{21}$$

where we have omitted the $n+\Delta$ time indices for the channel responses $\mathbf{h}$, $\hat{\mathbf{h}}$, $\mathbf{H}$, and $\hat{\mathbf{H}}$ for notational conciseness.

IV. Performance Comparisons

A. MMSE Performance

It was argued in section III-B that the MSE of all-tone prediction is less than pilot tone prediction. We shall determine that time-domain prediction is in turn better than all-tone prediction.

Rewriting (14) assuming $r_{H_k}(m) = r_h(m)$, and thus dropping the subscript k, we have

$$\begin{aligned}\varepsilon_{min,f} &= \frac{1}{N}\sum_{k=0}^{N-1}(r_h(0) - \mathbf{r}_\psi^H(\mathbf{R}_H + \sigma_{est}^2\mathbf{I})^{-1}\mathbf{r}_\psi)\\ &= 1 - \mathbf{r}_\psi^H(\mathbf{R}_H + \sigma_{est}^2\mathbf{I})^{-1}\mathbf{r}_\psi\end{aligned} \tag{22}$$

Taking the spectral decomposition [9] of $\mathbf{R}_H$, we have

$$\varepsilon_{min,f} = 1 - \sum_{l=0}^{p-1}\frac{\alpha_l}{\lambda_l + \sigma_{est}^2} \tag{23}$$

where $\alpha_l \triangleq \mathbf{r}_\psi^H\mathbf{v}_l\mathbf{v}_l^H\mathbf{r}_\psi$ and λ_ls are the eigenvalues of $\mathbf{R}_H$.

Similarly, for the MMSE of the time-domain prediction,

$$\begin{aligned}\varepsilon_{min,t} &= \frac{1}{N}\sum_{i=0}^{N_t-1}\left(r_{h_i}(0) - \mathbf{r}_{i,\psi}^H(\mathbf{R}_{h_i} + \sigma_{est}^2\mathbf{I})^{-1}\mathbf{r}_{i,\psi}\right)\\ &= \frac{1}{N}\sum_{i=0}^{N_t-1}\left(\sigma_i^2 r_h(0) - \sigma_i^2\mathbf{r}_\psi^H(\sigma_i^2\mathbf{R}_H + \sigma_{est}^2\mathbf{I})^{-1}\sigma_i^2\mathbf{r}_\psi\right)\\ &= \frac{1}{N}\sum_{i=0}^{N_t-1}\sigma_i^2\left(1 - \sum_{l=0}^{p-1}\frac{\sigma_i^2\alpha_l}{\sigma_i^2\lambda_l + \sigma_{est}^2}\right)\end{aligned} \tag{24}$$

Assuming a uniform power delay profile, i.e. $\sigma_i^2 = 1/N_t$, we have

$$\varepsilon_{min,t} = \frac{1}{N}\left(1 - \sum_{l=0}^{p-1}\frac{\alpha_l}{\lambda_l + \sigma_{est}^2 N_t}\right) \tag{25}$$

TABLE I

Computational complexity and memory requirements for the three proposed prediction algorithms

Algorithm	Computation	Memory
All-tone	$O(Np^2)$	$O(2Np)$
Pilot tone	$O(N_p p^2)$	$O(Np)$
Time-domain	$O(N_t p^2)$	$O(N_t p)$

Comparing the MMSE of both approaches, we have

$$\begin{aligned}\frac{\varepsilon_{min,f}}{\varepsilon_{min,t}} &= \frac{1 - \sum_{l=0}^{p-1}\frac{\alpha_l}{\lambda_l + \sigma_{est}^2}}{\frac{1}{N}\left(1 - \sum_{l=0}^{p-1}\frac{\alpha_l}{\lambda_l + \sigma_{est}^2 N_t}\right)}\\ &\approx N\end{aligned} \tag{26}$$

where the approximation is justified since σ_{est}^2 and N_t are typically small.

B. Computational Complexity and Memory Requirements

For the all-tone prediction, the optimum filter coefficients (9) can be solved using the Levinson recursion [9] which has complexity $O(p^2)$. Furthermore, $p+\psi$ autocorrelation lags need to be computed using (13), with M greater than p, and on the same order of magnitude as p. This gives a complexity of $O((p+\psi)^2)$. Since a separate filter is to be used for each subcarrier, the overall computational complexity is $O(N(p^2 + (p+\psi)^2)) \approx O(Np^2)$. On the other hand, N M-length previous channel estimates and N p-length prediction filters also need to be stored. This gives a memory complexity of $O(N(M+p)) \approx O(2Np)$.

In the pilot tone prediction, since we only need to design N_p prediction filters, the computational complexity is reduced by a factor of N/N_p to $O(N_p p^2)$. As for the memory required, we need to store N_p M-length previous channel estimates to compute the autocorrelations, $N - N_p$ p-length previous channel estimates for the prediction, and N_p p-length prediction filter coefficients. This gives a memory complexity of $O(p(N_p + N)) \approx O(Np)$, which is on the same order but half as complex as the all-tone case.

The complexity analysis of the time-domain prediction is similar to the pilot tone case, but with the added complexity of performing M N-IFFTs to get the time-domain responses for autocorrelation estimation and prediction, and one N-FFT to get back the predicted frequency response. This gives a computational complexity of $O(N_t Mp + N\log N(M+1)) \approx O(N_t p^2)$, which is still on the same order as the pilot tone case but more complex. The memory required, however, is less than the other two cases since we only need to store the channel estimates and filter coefficients for N_t taps, giving a complexity of $O(N_t(M+p)) \approx O(N_t p)$.

A summary of the computational complexity and memory requirements for the three proposed algorithms is provided in Table I.

C. Simulation Results

The OFDM system considered is based on the IEEE 802.16e mobile broadband wireless system [10] operating in the ETSI "Vehicular A" channel environment [11], which is a 6-tap frequency-selective Rayleigh fading channel model. It has $N = 256$ subcarriers, with $N_p = 8$ pilot tones, and a total of $N_d = 192$ data subcarriers, leaving $N_g = 56$ guard subcarriers. The system has bandwidth $BW = 5$ MHz and carrier frequency $f_c = 2.6$ GHz. A sampling frequency of $f_s = 144/125BW = 5.76$ MHz, and a guard interval of $N_{gi} = 64$ samples is used, giving an OFDM symbol period of $t_{sym} = (N + N_{gi})/f_s = 55.56\mu s$. We further assume a mobile velocity of $v = 75$ kph, giving a Doppler frequency of $f_d \approx 180Hz$, and a coherence time of $t_{coh} = 1/(2f_d) = 2.8$ ms, which is $n_{coh} \approx 50$ OFDM symbols.

The downsampling factor used for prediction is $d = 25$. This gives an effective prediction sampling rate of $f_p = 1/(t_{sym}d) = 720$ Hz, which is twice the required Nyquist sampling rate of $2f_d = 360$ Hz. The filter order is chosen to be $p = 75$ according to the minimum description length (MDL) cost function [9]. This value is in agreement with the typical model order defined in [12]. We assume we have $M = 100$ downsampled channel estimates to use to estimate the autocorrelations, which gives us information on approximately $Md/n_{coh} = 50$ coherence times in the past.

Figure 2 shows the normalized MSE performance of the three prediction schemes as the channel estimation error variance is increased for the case of predicting 1 and 5 t_{coh} ahead. It can be seen that the NMSE performance of the all-tone prediction is only slightly better than the pilot tone prediction, even if pilot tone prediction is less complex than all-tone prediction. Furthermore, time-domain prediction performs much better than the frequency domain prediction schemes. The improvement of time-domain prediction is more evident under high estimation errors, but lessens in lower estimation errors. Figure 3 shows the normalized MSE performance of the three prediction schemes as a function of the prediction horizon, the left figure for a high channel estimation error variance of $\sigma^2_{est} = 0.1$, and the right figure for a low estimation error variance $\sigma^2_{est} = 0.001$. We see the same performance differences across the three methods.

Intuitively, this is because the estimation error that was initially spread throughout the frequency domain channel response also spread throughout the time-domain channel taps through the IFFT operation. However, since we only do prediction on the highest energy taps, the error present in these taps is less than predicting on all the subcarriers in the frequency domain

V. Conclusion

We compared three different algorithms for long range channel prediction in OFDM systems: all-tone, pilot tone and time-domain prediction. Analytical and simulation results show that pilot tone prediction achieves almost the same NMSE performance with lower complexity than all-tone prediction. It was also shown that time-domain prediction has better NMSE performance than both other methods, while maintaining similar complexity as pilot tone prediction.

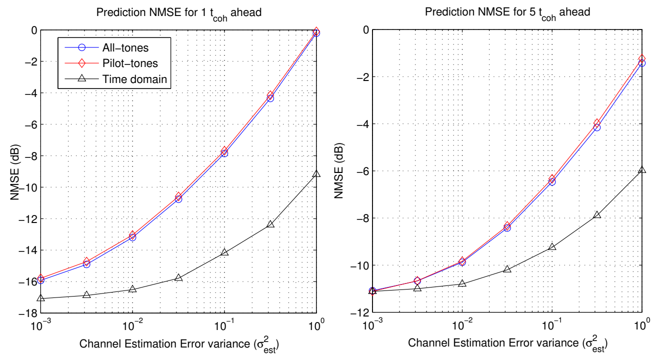

Fig. 2. NMSE performance of 3 approaches to OFDM channel prediction for varying channel estimation variances σ^2_{est}. Prediction for 1 t_{coh} ahead is shown at the left, and 5 t_{coh} ahead at the right figure. .

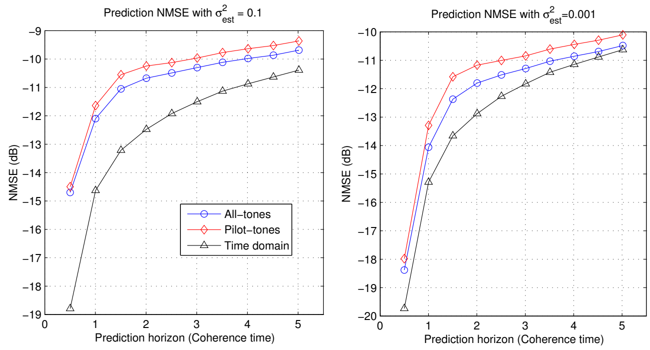

Fig. 3. NMSE performance of 3 approaches to OFDM channel prediction for varying prediction horizons. Prediction with $\sigma^2_{est} = 0.1$ is shown at the left, and $\sigma^2_{est} = 0.001$ is shown at the right. .

References

[1] S. Catreux, V. Erceg, D. Gesbert, and R. W. Heath, Jr., "Adaptive modulation and MIMO coding for broadband wireless data neworks," *IEEE Commun. Mag.*, vol. 40, no. 6, pp. 108–115, June 2002.

[2] M. R. Souryal and R. L. Pickholtz, "Adaptive modulation with imperfect channel information in OFDM," in *IEEE Proc. of Int. Conf. on Comm.*, June 2001, pp. 1861–1865.

[3] A. Forenza and R. W. Heath, Jr., "Link adaptation and channel prediction in wireless OFDM systems," in *Proc. 45th Midwest Symposium on Circuits and Systems*, August 2002, pp. 211–214.

[4] D. Schafhuber, G. Matz, and F. Hlawatsch, "Adaptive prediction of time-varying channels for coded OFDM systems," in *IEEE Proc. Int. Conf. on Acoustics, Signals, and Signal Processing*, May 2002, pp. 2549–2552.

[5] M. Sternad and D. Aronsson, "Channel estimation and prediction for adaptive OFDM downlinks," in *IEEE Vehicular Technology Conference*, Oct. 2003, pp. 1283 – 1287.

[6] T. S. Rappaport, *Wireless Communications: Principles and Practice, 2nd Ed.* Prentice Hall, Inc., 2002.

[7] Y. Li, N. Seshadri, and S. Ariyavisitakul, "Channel estimation for OFDM systems with transmitter diversity in mobile wireless channels," *IEEE J. Select. Areas Commun.*, vol. 17, no. 3, pp. 461–471, Mar. 1999.

[8] P. Hoeher, S. Kaiser, and I. Robertson, "Two-dimensional pilot-symbol-aided channel estimation by wiener filtering," in *Proc. Int. Conf. on Acoustics, Signals, and Signal Processing*, 1997, pp. 1845–1848.

[9] M. H. Hayes, *Statistical Digital Signal Processing and Modeling*. John Wiley and Sons, 1996.

[10] *Air Interface for Fixed and Mobile Broadband Wireless Access Systems*, IEEE Std. 802.16e/D5, Sept. 2004.

[11] *Selection procedures for the choice of radio transmission technologies for the UMTS*, ETSI Std. TR 101 112 v. 3.2.0, 1998.

[12] A. Duel-Hallen, S. Hu, and H. Hallen, "Long-range prediction of fading signals," *IEEE Signal Processing Magazine*, vol. 17, no. 3, pp. 62–75, May 2000.